A Unified Framework for Automatic Evaluation using N-gram Co-Occurrence Statistics

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Abstract

In this paper we propose a unified framework for automatic evaluation of NLP applications using N-gram co-occurrence statistics. The automatic evaluation metrics proposed to date for Machine Translation and Automatic Summarization are particular instances from the family of metrics we propose. We show that different members of the same family of metrics explain best the variations obtained with human evaluations, according to the application being evaluated (Machine Translation, Automatic Summarization, and Automatic Question Answering) and the evaluation guidelines used by humans for evaluating such applications.

1 Introduction

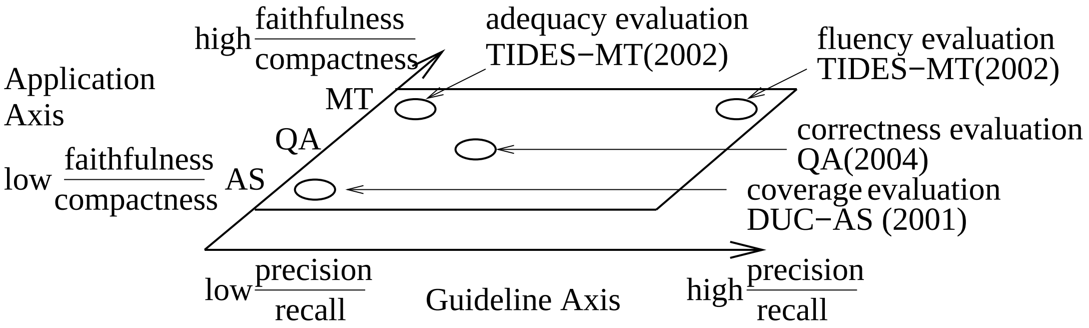
With the introduction of the BLEU metric for machine translation evaluation (Papineni et al, 2002), the advantages of doing automatic evaluation for various NLP applications have become increasingly appreciated: they allow for faster implement-evaluate cycles (by by-passing the human evaluation bottleneck), less variation in evaluation performance due to errors in human assessor judgment, and, not least, the possibility of hill-climbing on such metrics in order to improve system performance (Och 2003). Recently, a second proposal for automatic evaluation has come from the Automatic Summarization community (Lin and Hovy, 2003), with an automatic evaluation metric called ROUGE, inspired by BLEU but twisted towards the specifics of the summarization task.

An automatic evaluation metric is said to be successful if it is shown to have high agreement with human-performed evaluations. Human evaluations, however, are subject to specific guidelines given to the human assessors when performing the evaluation task; the variation in human judgment is therefore highly influenced by these guidelines. It follows that, in order for an automatic evaluation to agree with a human-performed evaluation, the evaluation metric used by the automatic method must be able to account, at least to some degree, for the bias induced by the human evaluation guidelines. None of the automatic evaluation methods proposed to date, however, explicitly accounts for the different criteria followed by the human assessors, as they are defined independently of the guidelines used in the human evaluations.

In this paper, we propose a framework for automatic evaluation of NLP applications which is able to account for the variation in the human evaluation guidelines. We define a family of metrics based on N-gram co-occurrence statistics, for which the automatic evaluation metrics proposed to date for Machine Translation and Automatic Summarization can be seen as particular instances. We show that different members of the same family of metrics explain best the variations obtained with human evaluations, according to the application being evaluated (Machine Translation, Automatic Summarization, and Question Answering) and the guidelines used by humans when evaluating such applications.

2 An Evaluation Plane for NLP

In this section we describe an evaluation plane on which we place various NLP applications evaluated using various guideline packages. This evaluation plane is defined by two orthogonal axes (see Figure 1): an *Application Axis*, on which we order NLP applications according to the faithfulness/compactness ratio that characterizes the application's input and output; and a *Guideline Axis*, on which we order various human guideline packages, according to the precision/recall ratio that characterizes the evaluation guidelines.



high faithfulness / compactness
Application Axis
low faithfulness / compactness
MT
QA
AS
adequacy evaluation TIDES−MT(2002)
fluency evaluation TIDES−MT(2002)
correctness evaluation QA(2004)
coverage evaluation DUC−AS (2001)
low precision / recall
Guideline Axis
high precision / recall

Figure 1: Evaluation plane for NLP applications

2.1 An Application Axis for Evaluation

When trying to define what translating and summarizing means, one can arguably suggest that a translation is some "as-faithful-as-possible" rendering of some given input, whereas a summary is some "as-compact-as-possible" rendering of some given input. As such, Machine Translation (MT) and Automatic Summarization (AS) are on the extremes of a faithfulness/compactness (f/c) ratio between inputs and outputs. In between these two extremes lie various other NLP applications: a high f/c ratio, although lower than MT's, characterizes Automatic Paraphrasing (paraphrase: To express, interpret, or translate *with latitude*); close to the other extreme, a low f/c ratio, although higher than AS's, characterizes Automatic Summarization with view-points (summarization which needs to focus on a given point of view, extern to the document(s) to be summarized). Another NLP application, Automatic Question Answering (QA), has arguably a close-to-1 f/c ratio: the task is to render an answer about the thing(s) inquired for in a question (the faithfulness side), in a manner that is concise enough to be regarded as a useful answer (the compactness side).

2.2 An Guideline Axis for Evaluation

Formal human evaluations make use of various guidelines that specify what particular aspects of the output being evaluated are considered important, for the particular application being evaluated. For example, human evaluations of MT (e.g., TIDES 2002 evaluation, performed by NIST) have traditionally looked at two different aspects of a translation: *adequacy* (how much of the content of the original sentence is captured by the proposed translation) and *fluency* (how correct is the proposed translation sentence in the target language). In many instances, evaluation guidelines can be linearly ordered according to the precision/recall (p/r) ratio they specify. For example, evaluation guidelines for *adequacy* evaluation of MT have a low p/r ratio, because of the high emphasis on recall (i.e., content is rewarded) and low emphasis on precision (i.e., verbosity is not penalized); on the other hand, evaluation guidelines for *fluency* of MT have a high p/r ratio, because of the low emphasis on recall (i.e., content is not rewarded) and high emphasis on wording (i.e., extraneous words are penalized). Another evaluation we consider in this paper, the DUC 2001 evaluation for Automatic Summarization (also performed by NIST), had specific guidelines for *coverage* evaluation, which means a low p/r ratio, because of the high emphasis on recall (i.e., content is rewarded). Last but not least, the QA evaluation for *correctness* we discuss in Section 4 has a close-to-1 p/r ratio for evaluation guidelines (i.e., both correct content and precise answer wording are rewarded).

When combined, the application axis and the guideline axis define a plane in which particular evaluations are placed according to their application/guideline coordinates. In Figure 1 we illustrate this evaluation plane, and the evaluation examples mentioned above are placed in this plane according to their coordinates.

3 A Unified Framework for Automatic Evaluation

In this section we propose a family of evaluation metrics based on N-gram co-occurrence statistics. Such a family of evaluation metrics provides flexibility in terms of accommodating both various NLP applications and various values of precision/recall ratio in the human guideline packages used to evaluate such applications.

3.1 A Precision-focused Family of Metrics

Inspired by the work of Papineni et al. (2002) on BLEU, we define a precision-focused family of metrics, using as parameter a non-negative integer *N*. Part of the definition includes a list of stop-words (*SW*) and a function for extracting the stem of a given word (*ST*).

Suppose we have a given NLP application for which we want to evaluate the candidate answer set *Candidates* for some input sequences, given a reference answer set *References*. For each individual candidate answer *C*, we define *S(C,n)* as the multi-set of *n*-grams obtained from the candidate answer *C* after stemming the unigrams using *ST* and eliminating the unigrams found in *SW*. We therefore define a precision score:

$$P(n) = \frac{\sum_{C \in \{Candidates\}} \sum_{ngram \in S(C,n)} Count_{clip}(ngram)}{\sum_{C \in \{Candidates\}} \sum_{ngram \in S(C,n)} Count(ngram)}$$

where *Count(ngram)* is the number of *n*-gram counts, and $Count_{clip}(ngram)$ is the maximum number of co-occurrences of *ngram* in the candidate answer and its reference answer. Because the denominator in the *P(n)* formula consists of a sum over the proposed candidate answers, this formula is a precision-oriented formula, penalizing verbose candidates. This precision score, however, can be made artificially higher when proposing shorter and shorter candidate answers. This is offset by adding a brevity penalty, *BP*:

$$BP = \begin{cases} 1, & if \quad B \cdot |c| \geq |r| \\ e^{(1-|r|/B|c|)}, & if \quad B \cdot |c| < |r| \end{cases}$$

where |*c*| equals the sum of the lengths of the proposed answers, |*r*| equals the sum of the lengths of the reference answers, and *B* is a brevity constant.

We define now a precision-focused family of metrics, parameterized by a non-negative integer *N*, as:

$$PS(N) = BP \cdot \exp(\sum_{n=1}^{N} w_n \log(P(n)))$$

This family of metrics can be interpreted as a weighted linear average of precision scores for increasingly longer *n*-grams. As the values of the precision scores decrease roughly exponentially with the increase of *N*, the logarithm is needed to obtain a linear average. Note that the metrics of this family are well-defined only for *N*'s small enough to yield non-zero *P(n)* scores. For test corpora of reasonable size, the metrics are usually well-defined for $N \leq 4$.

The BLEU proposed by Papineni et al. (2002) for automatic evaluation of machine translation is part of the family of metrics *PS(N)*, as the particular metric obtained when *N*=4, w_n–s are 1/*N*, the brevity constant *B*=1, the list of stop-words *SW* is empty, and the stemming function *ST* is the identity function.

3.2 A Recall-focused Family of Metrics

As proposed by Lin and Hovy (2003), a precision-focused metric such as BLEU can be twisted such that it yields a recall-focused metric. In a similar manner, we define a recall-focused family of metrics, using as parameter a non-negative integer *N*, with a list of stop-words (*SW*) and a function for extracting the stem of a given word (*ST*) as part of the definition.

As before, suppose we have a given NLP application for which we want to evaluate the candidate answer set *Candidates* for some input sequences, given a reference answer set *References*. For each individual reference answer *R*, we define *S(R,n)* as the multi-set of *n*-grams obtained from the reference answer *R* after stemming the unigrams using *ST* and eliminating the unigrams found in *SW*. We therefore define a recall score as:

$$R(n) = \frac{\sum_{R \in \{References\}} \sum_{ngram \in S(R,n)} Count_{clip}(ngram)}{\sum_{R \in \{References\}} \sum_{ngram \in S(R,n)} Count(ngram)}$$

where, as before, *Count(ngram)* is the number of *n*-gram counts, and $Count_{clip}(ngram)$ is the maximum number of co-occurrences of *ngram* in the reference answer and its corresponding candidate answer. Because the denominator in the *R(n)* formula consists of a sum over the reference answers, this formula is essentially a recall-oriented formula, which penalizes incomplete candidates. This recall score, however, can be made artificially higher when proposing longer and longer candidate answers. This is offset by adding a wordiness penalty, *WP*:

$$WP = \begin{cases} 1, & if \quad W \cdot |c| \leq |r| \\ e^{(1-W|c|/|r|)}, & if \quad W \cdot |c| > |r| \end{cases}$$

where |*c*| and |*r*| are defined as before, and *W* is a wordiness constant.

We define now a recall-focused family of metrics, parameterized by a non-negative integer *N*, as:

$$RS(N) = WP \cdot \exp(\sum_{n=1}^{N} w_n \log(R(n)))$$

This family of metrics can be interpreted as a weighted linear average of recall scores for increasingly longer n-grams. For test corpora of reasonable size, the metrics are usually well-defined for $N \leq 4$.

The ROUGE metric proposed by Lin and Hovy (2003) for automatic evaluation of machine-produced summaries is part of the family of metrics *RS(N)*, as the particular metric obtained when *N*=1, w_n–s are 1/*N*, the wordiness constant *W*=∞, the list of stop-words *SW* is their own , and the stemming function *ST* is the one defined by the Porter stemmer (Porter 1980).

3.3 A Unified Framework for Automatic Evaluation

The precision-focused metric family *PS(N)* and the recall-focused metric family *RS(N)* defined in the previous sections are unified under the metric family *AEv*(α,*N)*, defined as:

$$AEv(\alpha,N)=\frac{RS(N)PS(N)}{\alpha\cdot RS(N)+(1-\alpha)\cdot PS(N)}$$

This formula extends the well-known F-measure that combines recall and precision numbers into a single number (van Rijsbergen, 1979), by combining recall and precision metric families into a single metric family. For α=0, *AEv*(α,*N)* is the same as the recall-focused family of metrics *RS(N)*; for α=1, *AEv*(α,*N)* is the same as the precision-focused family of metrics *PS(N)*. For α in between 0 and 1, *AEv*(α,*N)* are metrics that balance recall and precision according to α. For the rest of the paper, we restrict the parameters of the *AEv*(α*,N)* family as follows: α varies continuously in [0,1], *N* varies discretely in {1,2,3,4}, the linear weights w_n are 1/*N*, the brevity constant is 1, the wordiness constant is 2, the list of stop-words *SW* is our own 626 stop-word list, and the stemming function *ST* is the one defined by the Porter stemmer (Porter 1980).

We establish a correspondence between the parameters of the family of metrics *AEv*(α*,N)* and the evaluation plane in Figure 1 as follows: α parameterizes the guideline axis (x-axis) of the plane, such that α=0 corresponds to a low precision/recall (p/r) ratio, and α=1 corresponds to a high p/r ratio; *N* parameterizes the application axis (y-axis) of the plane, such that *N*=1 corresponds to a low faithfulness/compactness (f/c) ratio (unigram statistics allow for a low representation of faithfulness, but a high representation of compactness), and *N*=4 corresponds to a high f/c ratio (n-gram statistics up to 4-grams allow for a high representation of faithfulness, but a low representation of compactness).

This framework enables us to predict that a human-performed evaluation is best approximated by metrics that have similar f/c ratio as the application being evaluated and similar p/r ratio as the evaluation package used by the human assessors. For example, an application with a high f/c ratio, evaluated using a low p/r ratio evaluation guideline package (an example of this is the *adequacy* evaluation for MT in TIDES 2002), is best approximated by the automatic evaluation metric defined by a low α and a high *N*; an application with a close-to-1 f/c ratio, evaluated using an evaluation guideline package characterized by a close-to-1 p/r ratio (such as the *correctness* evaluation for Question Answering in Section 4.3) is best approximated by an automatic metric defined by a median α and a median *N*.

4 Evaluating the Evaluation Framework

In this section, we present empirical results regarding the ability of our family of metrics to approximate human evaluations of various applications under various evaluation guidelines.

We measure the amount of approximation of a human evaluation by an automatic evaluation as the value of the coefficient of determination R^2 between the human evaluation scores and the automatic evaluation scores for various systems implementing Machine Translation, Summarization, and Question Answering applications. In this framework, the coefficient of determination R^2 is to be interpreted as the percentage from the total variation of the human evaluation (that is, why some system's output is better than some other system's output, *from the human evaluator's perspective*) that is captured by the automatic evaluation (that is, why some system's output is better than some other system's output, *from the automatic evaluation perspective*). The values of R^2 vary between 0 and 1, with a value of 1 indicating that the automatic evaluation explains perfectly the human evaluation variation, and a value of 0 indicating that the automatic evaluation explains nothing from the human evaluation variation. All the results for the values of R^2 for the family of metrics *AEv*(α*,N)* are reported with α varying from 0 to 1 in 0.1 increments, and *N* varying from 1 to 4.

4.1 Machine Translation Evaluation

The Machine Translation evaluation carried out by NIST in 2002 for DARPA's TIDES programme involved 7 systems that participated in the Chinese-English track. Each system was evaluated by a human judge, using one reference extracted from a list of 4 available reference translations. Each of the 878 test sentences was evaluated both for *adequacy* (how much of the content of the original sentence is captured by the proposed translation) and *fluency* (how correct is the proposed translation sentence in the target language). From the publicly available data for this evaluation (TIDES 2002), we compute the values of R^2 for 7 data points (corresponding to the 7 systems participating in the Chinese-English track), using as a reference set one of the 4 sets of reference translations available.

In Table 1, we present the values of the coefficient of determination R^2 for the family of metrics *AEv*(α,*N)*, when considering only the *fluency* scores from the human evaluation. As mentioned in Section 2, the evaluation guidelines for *fluency* have a high precision/recall ratio, whereas MT is an application with a high

4	76.10	76.45	76.78	77.10	77.40	77.69	77.96	78.21	78.45	78.67	**78.87**
3	76.11	76.6	77.04	77.44	77.80	78.11	78.38	78.61	78.80	**78.94**	**79.04**
2	73.19	74.21	75.07	75.78	76.32	76.72	76.96	77.06	77.03	76.87	76.58
1	31.71	38.22	44.82	51.09	56.59	60.99	64.10	65.90	66.50	66.12	64.99
N/α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Table 1: R^2 values for the family of metrics *AEv*(α,*N)*, for *fluency* scores in MT evaluation

4	**83.04**	82.58	82.11	81.61	81.10	80.56	80.01	79.44	78.86	78.26	77.64
3	81.80	81.00	80.16	79.27	78.35	77.39	76.40	75.37	74.31	73.23	72.11
2	80.84	79.46	77.94	76.28	74.51	72.63	70.67	68.64	66.55	64.42	62.26
1	62.16	66.26	69.18	70.59	70.35	68.48	65.24	60.98	56.11	50.98	45.88
N/α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Table 2: R^2 values for the family of metrics *AEv*(α,*N)*, for *adequacy* scores in MT evaluation

faithfulness/compactness ratio. In this case, our evaluation framework predicts that the automatic evaluation metrics that explain most of the variation in the human evaluation must have a high α and a high *N*. As seen in Table 1, our evaluation framework correctly predicts the automatic evaluation metrics that explain most of the variation in the human evaluation: metrics *AEv*(1,3), *AEv*(0.9,3), and *AEv*(1,4) capture most of the variation: 79.04%, 78.94%, and 78.87%, respectively. Since metric *AEv*(1,4) is almost the same as the BLEU metric (modulo stemming and stop word elimination for unigrams), our results confirm the current practice in the Machine Translation community, which commonly uses BLEU for automatic evaluation. For comparison purposes, we also computed the value of R^2 for *fluency* using the BLEU score formula given in (Papineni et al., 2002), for the 7 systems using the same one reference, and we obtained a similar value, 78.52%; computing the value of R^2 for *fluency* using the BLEU scores computed with all 4 references available yielded a lower value for R^2, 64.96%, although BLEU scores obtained with multiple references are usually considered more reliable.

In Table 2, we present the values of the coefficient of determination R^2 for the family of metrics *AEv*(α,*N)*, when considering only the *adequacy* scores from the human evaluation. As mentioned in Section 2, the evaluation guidelines for *adequacy* have a low precision/recall ratio, whereas MT is an application with high faithfulness/compactness ratio. In this case, our evaluation framework predicts that the automatic evaluation metrics that explain most of the variation in the human evaluation must have a low α and a high *N*. As seen in Table 2, our evaluation framework correctly predicts the automatic evaluation metric that explains most of the variation in the human evaluation: metric *AEv*(0,4) captures most of the variation, 83.04%. For comparison purposes, we also computed the value of R^2 for *adequacy* using the BLEU score formula given in (Papineni et al., 2002), for the 7 systems using the same one reference, and we obtain a similar value, 83.91%; computing the value of R^2 for *adequacy* using the BLEU scores computed with all 4 references available also yielded a lower value for R^2, 62.21%.

4.2 Automatic Summarization Evaluation

The Automatic Summarization evaluation carried out by NIST for the DUC 2001 conference involved 15 participating systems. We focus here on the multi-document summarization task, in which 4 generic summaries (of 50, 100, 200, and 400 words) were required for a given set of documents on a single subject. For this evaluation 30 test sets were used, and each system was evaluated by a human judge using one reference extracted from a list of 2 reference summaries. One of the evaluations required the assessors to judge the *coverage* of the summaries. The *coverage* of a summary was measured by comparing a system's units versus the units of a reference summary, and assessing whether each system unit expresses *all, most, some, hardly any*, or *none* of the current reference unit. A final evaluation score for *coverage* was obtained using a coverage score computed as a weighted recall score (see (Lin and Hovy 2003) for more information on the human summary evaluation). From the publicly available data for this evaluation (DUC 2001), we compute the values of R^2 for 15 data points available (corresponding to the 15 participating systems).

In Tables 3-4 we present the values of the coefficient of determination R^2 for the family of metrics *AEv*(α,*N)*, when considering the *coverage*

4	67.10	66.51	65.91	65.29	64.65	64.00	63.34	62.67	61.99	61.30	60.61
3	69.55	68.81	68.04	67.24	66.42	65.57	64.69	63.79	62.88	61.95	61.00
2	74.43	73.29	72.06	70.74	69.35	67.87	66.33	64.71	63.03	61.30	59.51
1	**90.77**	**90.77**	90.66	90.42	90.03	89.48	88.74	87.77	86.55	85.05	83.21
N/α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Table 3: R^2 for the family of metrics *AEv*(α,*N)*, for coverage scores in AS evaluation (200 words)

4	81.24	81.04	80.78	80.47	80.12	79.73	79.30	78.84	78.35	77.84	77.31
3	84.72	84.33	83.86	83.33	82.73	82.08	81.39	80.65	79.88	79.07	78.24
2	89.54	88.56	87.47	86.26	84.96	83.59	82.14	80.65	79.10	77.53	75.92
1	**92.28**	91.11	89.70	88.07	86.24	84.22	82.05	79.74	77.30	74.77	72.15
N/α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Table 4: R^2 for the family of metrics *AEv*(α,*N)*, for *coverage* scores in AS evaluation (400 words)

scores from the human evaluation, for summaries of 200 and 400 words, respectively (the values of R^2 for summaries of 50 and 100 words show similar patterns). As mentioned in Section 2, the evaluation guidelines for *coverage* have a low precision/recall ratio, whereas AS is an application with low faithfulness/compactness ratio. In this case, our evaluation framework predicts that the automatic evaluation metrics that explain most of the variation in the human evaluation must have a low α and a low *N*. As seen in Tables 3-4, our evaluation framework correctly predicts the automatic evaluation metric that explain most of the variation in the human evaluation: metric *AEv*(0,1) explains 90.77% and 92.28% of the variation in the human evaluation of summaries of length 200 and 400, respectively. Since metric *AEv*(0, 1) is almost the same as the ROUGE metric proposed by Lin and Hovy (2003) (they only differ in the stop-word list they use), our results also confirm the proposal for such metrics to be used for automatic evaluation by the Automatic Summarization community.

4.3 Question Answering Evaluation

One of the most common approaches to automatic question answering (QA) restricts the domain of questions to be handled to so-called factoid questions. Automatic evaluation of factoid QA is often straightforward, as the number of correct answers is most of the time limited, and exhaustive lists of correct answers are available. When removing the factoid constraint, however, the set of possible answer to a (complex, beyond-factoid) question becomes unfeasibly large, and consequently automatic evaluation becomes a challenge.

In this section, we focus on an evaluation carried out in order to assess the performance of a QA system for answering questions from the Frequently-Asked-Question (FAQ) domain (Soricut and Brill, 2004). These are generally questions requiring a more elaborated answer than a simple factoid (e.g., questions such as: "How does a film qualify for an Academy Award?").

In order to evaluate such a system a human-performed evaluation was performed, in which 11 versions of the QA system (various modules were implemented using various algorithms) were separately evaluated. Each version was evaluated by a human evaluator, with no reference answer available. For this evaluation 115 test questions were used, and the human evaluator was asked to assess whether the proposed answer was *correct, somehow related*, or *wrong*. A unique ranking number was achieved using a weighted average of the scored answers. (See (Soricut and Brill, 2004) for more details concerning the QA task and the evaluation procedure.)

One important aspect in the evaluation procedure was devising criteria for assigning a rating to an answer which was not neither *correct* nor *wrong*. One of such cases involved so-called flooded answers: answers which contain the correct information, along with several other unrelated pieces of information. A first evaluation has been carried with a guideline package asking the human assessor to assign the rating *correct* to flooded answers. In Table 5, we present the values of the coefficient of determination R^2 for the family of metrics *AEv*(α,*N)* for this first QA evaluation. On the guideline side, the guideline package used in this first QA evaluation has a low precision/recall ratio, because the human judge is asked to evaluate based on the content provided by a given answer (high recall), but is asked to disregard the conciseness (or lack thereof) of the answer (low precision); consequently, systems that focus on

4	63.40	57.62	51.86	46.26	40.96	36.02	31.51	27.43	23.78	20.54	17.70
3	81.39	76.38	70.76	64.76	58.61	52.51	46.63	41.09	35.97	31.33	27.15
2	**91.72**	89.21	85.54	80.78	75.14	68.87	62.25	55.56	49.04	42.88	37.20
1	61.61	58.83	55.25	51.04	46.39	41.55	36.74	32.12	27.85	23.97	20.54
N/α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Table 5: R^2 for the family of metrics *AEv*(α,*N)*, for *correctness* scores, first QA evaluation

4	79.94	79.18	75.80	70.63	64.58	58.35	52.39	46.95	42.11	37.87	34.19
3	76.15	80.44	81.19	78.45	73.07	66.27	59.11	52.26	46.08	40.68	36.04
2	67.76	77.48	84.34	**86.26**	82.75	75.24	65.94	56.65	48.32	41.25	35.42
1	56.55	60.81	59.60	53.56	45.38	37.40	30.68	25.36	21.26	18.12	15.69
N/α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Table 6: R^2 for the family of metrics *AEv*(α,*N)*, for *correctness* scores, second QA evaluation

giving correct and concise answers are not distinguished from systems that give correct answers, but have no regard for concision. On the application side, as mentioned in Section 2, QA is arguably an application characterized by a close-to-1 faithfulness/compactness ratio. In this case, our evaluation framework predicts that the automatic evaluation metrics that explain most of the variation in the human evaluation must have a low α and a median *N*. As seen in Table 5, our evaluation framework correctly predicts the automatic evaluation metric that explain most of the variation in the human evaluation: metric *AEv*(0,2) explains most of the human variation, 91.72%. Note that other members of the *AEv*(α,*N)* family do not explain nearly as well the variation in the human evaluation. For example, the ROUGE-like metric *AEv*(0,1) explains only 61.61% of the human variation, while the BLEU-like metric *AEv*(1,4) explains a mere 17.7% of the human variation (to use such a metric in order to automatically emulate the human QA evaluation is close to performing an evaluation assigning random ratings to the output answers).

In order to further test the prediction power of our evaluation framework, we carried out a second QA evaluation, using a different evaluation guideline package: a flooded answer was rated only *somehow-related*. In Table 6, we present the values of the coefficient of determination R^2 for the family of metrics *AEv*(α,*N)* for this second QA evaluation. Instead of performing this second evaluation from scratch, we actually simulated it using the following methodology: 2/3 of the output answers rated *correct* of the systems ranked 1st, 2nd, 3rd, and 6th by the previous human evaluation have been intentionally over-flooded using two long and out-of-context sentences, while their ratings were changed from *correct* to *somehow-related*. Such a change simulated precisely the change in the guideline package, by downgrading flooded answers. This means that, on the guideline side, the guideline package used in this second QA evaluation has a close-to-1 precision/recall ratio, because the human judge evaluates now based both on the content and the conciseness of a given answer. At the same time, the application remains unchanged, which means that on the application side we still have a close-to-1 faithfulness/compactness ratio. In this case, our evaluation framework predicts that the automatic evaluation metrics that explain most of the variation in the human evaluation must have a median α and a median *N*. As seen in Table 6, our evaluation framework correctly predicts the automatic evaluation metric that explain most of the variation in the human evaluation: metric *AEv*(0.3,2) explains most of the variation in the human evaluation, 86.26%. Also note that, while the R^2 values around *AEv*(0.3,2) are still reasonable, evaluation metrics that are further and further away from it have increasingly lower R^2 values, meaning that they are more and more unreliable for this task. The high correlation of metric *AEv*(0.3,2) with human judgment, however, suggests that such a metric is a good candidate for performing automatic evaluation of QA systems that go beyond answering factoid questions.

5 Conclusions

In this paper, we propose a unified framework for automatic evaluation based on N-gram co-occurrence statistics, for NLP applications for which a correct answer is usually an unfeasibly large set (e.g., Machine Translation, Paraphrasing, Question Answering, Summarization, etc.). The success of BLEU in doing automatic evaluation of machine translation output has often led researchers to blindly try to use this metric for evaluation tasks for which it was more or less appropriate (see, e.g., the paper of Lin and Hovy (2003), in which the authors start with the assumption that BLEU might work for summarization evaluation, and discover after several trials a better candidate).

Our unifying framework facilitates the understanding of when various automatic evaluation metrics are able to closely approximate human evaluations for various applications. Given an application *app* and an evaluation guideline package *eval*, the faithfulness/compactness ratio of the application and the precision/recall ratio of the evaluation guidelines determine a restricted area in the evaluation plane in Figure 1 which best characterizes the (*app*, *eval*) pair. We have empirically demonstrated that the metrics from the *AEv*(α,*N)* family that best approximate human judgment are those that have the α and *N* parameters in the determined restricted area. To our knowledge, this is the first proposal regarding automatic evaluation in which the automatic evaluation metrics are able to account for the variation in human judgment due to specific evaluation guidelines.

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